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Uncertainty assessment of satellite remote-sensing-based evapotranspiration estimates: a systematic review of methods and gaps

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S2. Bibliometric analyses of included articles

Figure S1 shows the increasing number of articles resulting from the search queries in from 2011 to 2021 (the last access: 24/07/2023). The proportion of records when including the variants of the ‘uncertainty’ search term was about 60% and did not change considerably with the years. This proportion indicates that “uncertainty” has been playing a stable and important role in the studies of remotely sensed evapotranspiration.

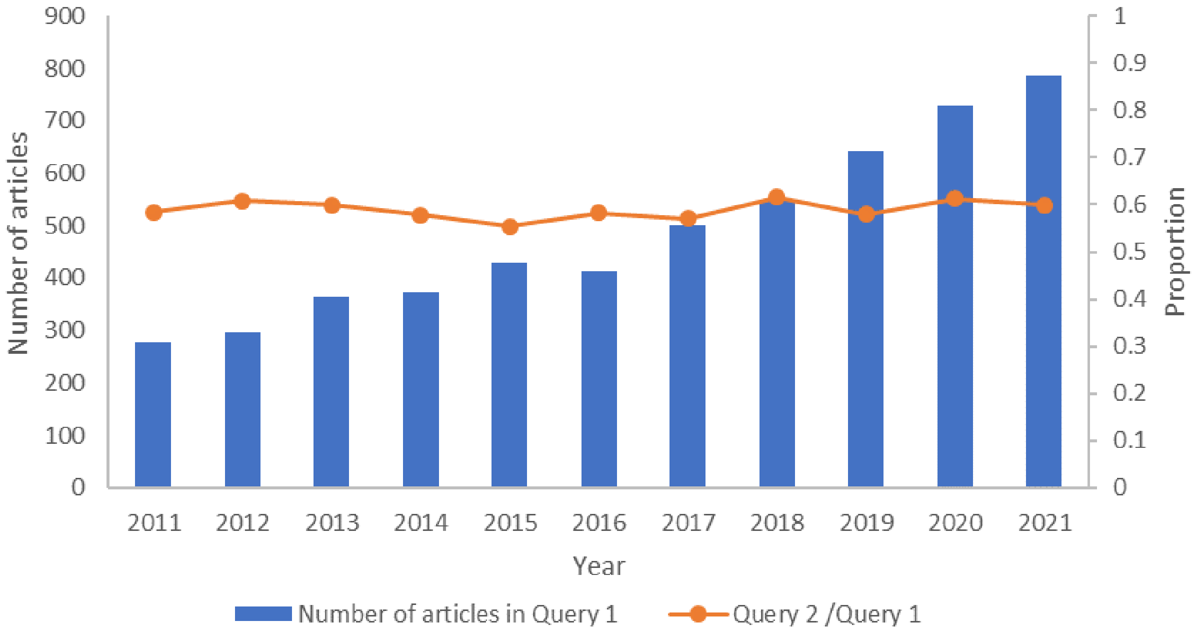

Figure S1: The number of records from search query 1 which includes variants of “Remote sensing”, “evapotranspiration”, and “Uncertainty” search terms, and the proportion of records from query 1 over records from query 2 which excludes ‘Uncertainty’ search terms.

The articles included in the quantitative synthesis were published in 134 journals. shows the journals with the most articles included. Altogether, these journals made up about 62% of the total articles. *Remote Sensing (MDPI)* ranked first with 101 articles (16.8% of the total, indicating that uncertainty in

RS-ET is discussed more in remote sensing than in agriculture and hydrology journals, which are the main fields where RS-ET is applied.

Table S1: The journals with the most included articles.

No.	Journal	Number of articles	% of all included articles
1	Remote Sensing (MDPI)	114	16.9%
2	Remote Sensing of Environment	48	7.1%
3	Agricultural and Forest Meteorology	39	5.8%
4	Hydrology and Earth System Sciences	33	4.9%
5	Journal of Hydrology	33	4.9%
6	International Journal of Remote Sensing	31	4.6%
7	Agricultural Water Management	26	3.8%
8	Water Resources Research	22	3.3%
9	Water (MDPI)	16	2.4%
10	Journal of Applied Remote Sensing	14	2.1%
11	International Journal of Applied Earth Observation and Geoinformation	12	1.8%
12	Hydrological Processes	10	1.5%
13	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	10	1.5%
14	Hydrological Sciences Journal	7	1.0%
15	Advances in Meteorology	5	0.7%
	Other journals		37.9%

Figure S2 shows the co-author network of the included articles. The size of the circle represents the number of articles per author, with a threshold of at least 10 articles per author. The links represent the number of studies each collaborated in. Each cluster is often led by the first author of a particular RS-ET model. For example, Anderson M.C and Kustas W.P. have published mainly about ALEXI and TSEB models, Senay G.B. about SSEBop, Fisher J.B. about PT-JPL, and Miralles D.G. about GLEAM. The clusters of Yao Y., Zhang X., Chen X., and co-authors had more publications in later years (with an average publication year > 2017).

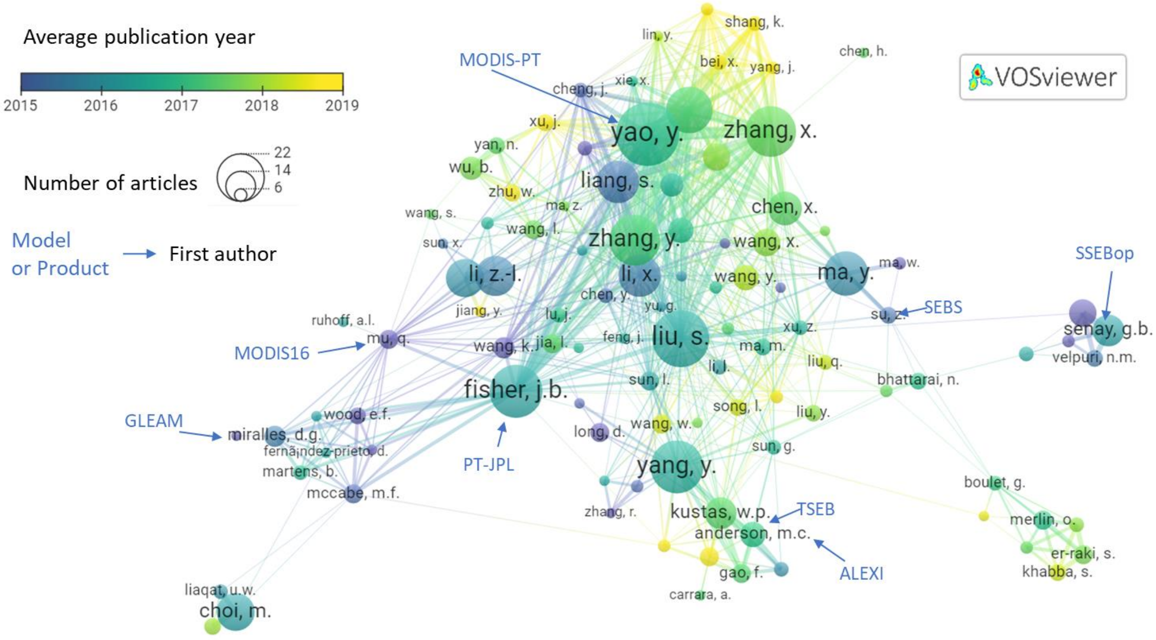

Figure S2: Network of co-authors of included articles (N=676) and the average year of publication generated using VOSviewer software (Eck and Waltman, 2009)

S3. Main topics of the previous literature reviews

Table S2: Main topics of the previous literature reviews on RS-derived ET estimation and the uncertainty and validation of spatial data and RS-derived data in general

Topic	References	Focus of the review
ET estimation methods based on satellite data	Kustas and Norman, 1996	Describing techniques used in evaluating ET with remote sensing at hourly to daily time frame, with a summary of 16 model types.
	Courault et al., 2005	Reviewing different approaches to estimate ET from remote sensing data and discussing the main physical bases and assumptions of various models, and proposing to classifying methods into 4 categories: empirical direct, residual of energy balance, deterministic, and vegetation index methods.
	Gowda et al., 2007	Reviewing 6 common remote sensing-based land surface energy balance algorithms for mapping regional ET and their limitations, data needs, knowledge gaps, and future opportunities and challenges with respect to agriculture.
	Kalma et al., 2008	Reviewing methods for estimating evaporation from landscapes, regions, and larger geographic extents, with remotely sensed surface temperatures, and highlighting uncertainties and limitations associated with those estimation methods based on the results of 30 validation studies.
	Li et al., 2009	Providing an overview of 10 commonly applied ET models using remotely sensed data in terms of theories, inputs, assumptions, the

		accuracy of results, and advantages and drawbacks of models.
	Glenn et al., 2007	Emphasizing combination of RS and ground methods for estimating ET over a region and its limitation, accuracy, and future improvements.
	Glenn et al., 2010	Examining the role and utility of methods that use Vegetation Indices (VI) from satellites to estimate ET over a wide range of scales of measurements, discussing limitations and accuracy of these methods.
	Liang et al., 2010	Reviewing the recent advances in estimating evapotranspiration and other variables in land surface radiation and energy budgets using remote sensing, ground measurements, and numerical models.
	Glenn et al., 2011	Reviewing ground methods used to estimate local ET and remote sensing methods developed for regional and continental scales, also discussing sources of error or uncertainty inherent in the estimates, lessons learned from ET research in Australia
	Senay et al., 2011	Reviewing methods to estimate basin-scale ET, including satellite-based methods
	Wang and Dickinson, 2012	Surveying the basic theories, observational methods, satellite algorithm and land surface models for terrestrial ET
	Liou and Kar, 2014	Reviewing 6 common surface energy balance algorithms regarding their main assumptions, advantages and disadvantages.
	Zhang et al., 2016	Summarizing the underlying theories, development history, advantages and limitations of 7 groups of remote sensing based evapotranspiration estimation methods
	Mohan et al., 2020	Summarizing approaches to estimate sensible heat flux in RS-ET models
	Chen and Liu, 2020	Providing key milestones in history of remote sensing ET model development in 2 categories: temperature-based and conductance-based models
	García-Santos et al., 2022	Reviewing the current advances of the common algorithms to estimate ET from satellite Land Surface Temperature with a summary of presentative validation studies.
Uncertainty and validation of spatial data and RS-derived data in general	Zeng et al., 2015	Assessing how European initiatives approach the validation of Essential Climate Variables (ECVs) Climate Data Records (CDRs) with 3 examples of soil moisture, fAPAR and sea ice; discussing aspects of validation process and proposing a generic validation process for ECVs CDRs
	Mayr et al., 2019	Reviewing validation of temporally dense time-series of land surface geo-information products that cover the continental to global scale, in terms of utilized validation data, validation methods, development trend.
	Wu et al., 2019	Reviewing the development of validation methodologies worldwide in terms of principles and approaches, recent progress of validation in

		China, the shortcomings of the current status of validation; providing outlook and forecasting development trend of validation
	Bielecka and Burek, 2019	Providing a survey on spatial data quality and uncertainty research production in the last 30 years, highlighting that remote sensing and geography were the main research subject categories where quality and uncertainty are of greatest importance at all stages from data acquisition to information retrieval.
	Bayat et al., 2021	Investigating level of readiness for operation validation of 7 global long-term satellite-based terrestrial ECVs including ET
Uncertainty or accuracy of ET estimation	Allen et al., 2011a	Describing common ET measuring systems including *in situ* and remote sensing techniques, and the sources and typical range of their errors.
	Allen et al., 2011b	Providing recommendations for documentation and description of information that should accompany ET estimates reported in ET-related articles.
	Karimi and Bastiaanssen , 2015	Reviewing the reliability of remote sensing algorithms to accurately determine the spatial distribution of ET (and rainfall and land use) by synthesizing mean error of seasonal ET reported in 31 papers that use remote sensing ET algorithms.

S4. In situ methods to measure Evapotranspiration (ET) or Latent Heat Flux (LE)

Table S3: In situ methods to measure Evapotranspiration (ET) or Latent Heat Flux (LE). N/A: Not Applicable

Method	**Instruments**	**Measurement**	**Intermediate calculations**	**Method to derive ET or LE**
Eddy covariance (EC)	Infrared Gas Analyser (IRGA)	Water vapor concentration	Calculation of mixing ratio of water vapor and dry air	Derivation of LE from eddy covariance using Reynolds averaging (Foken et al., 2012; Montgomery, 1948)
	Sonic anemometer	3-direction wind speed	Calculation of covariance of vertical wind velocity and mixing ratio	
Lysimetry	Weighing lysimeter, Drainage lysimeter or Soil water content sensor (e.g. neutron probe)	Soil weight or Soil water content	Calculation of change in soil water storage	Derivation of ET as residual of soil water balance (e.g., Teuling, 2018)
	Rain gauge	Rainfall	Calculation of water inflow	
	Flow meter	Irrigation		
Scintillometry	Large Aperture Scintillometer (LAS) - Transmitter	Log-variance of the intensity variations	Calculation of structure parameters of refractive	Derivation of sensible heat (H) and Latent heat flux

	- Detector	of the received light beam signals	index, temperature, specific humidity	(LE) based on Monin-Obukhov Similarity Theory (Frehlich, 1992; Hill, 1997)
	Temperature probe	Air temperature at different heights	Determination of sensible heat (H) direction based on temperature gradient	
Bowen ratio energy balance (BREB)	Temperature probe, Relative humidity probe, Barometer	Gradient of atmospheric temperature, air moisture content (actual water vapor pressure)	Calculation of Bowen ratio	Derivation of H and LE from Bowen ratio and surface energy balance
	Net radiometer, Wind speed and direction sensor	Net radiation	Calculation of sum of H and LE from surface energy balance equation	
	Soil heat flow plates, Soil moisture probe	Soil heat flux		
Surface renewal (SR)	Fine-wire thermocouple	High frequency temperature fluctuation	Calculation of sensible heat (H) based on a solution of the scalar conservation	Derivation of LE as residual of surface energy balance (Paw U et al., 1995)
	Net radiometer, Wind speed and direction sensor	Net radiation	Calculation of sum of H and LE from surface energy balance equation	
	Soil heat flow plates, Soil moisture probe	Soil heat flux		
Advection-aridity (AA)	Anemometer Pressure sensor Thermometer Hygrometer	Windspeed Air pressure Air temperature Relative humidity	Calculation of wet surface ET (P-T), potential ET (Penman), and relative evaporation	Derivation of ET based on complementary relationship (Brutsaert and Stricker, 1979)
Combinatory method (CM)	Anemometer Pressure sensor Thermometer Hygrometer	Windspeed Air pressure Air temperature Relative humidity	Calculation of LE and H without stability correction	Derivation of LE using stability correction (Thom et al., 1975; Zhong et al., 2019)
	Temperature probe, Net radiometer	Net radiation Soil heat flux	Calculation of stability function	
FAO-56 Crop coefficient	Net radiometer Anemometer Pressure sensor Thermometer Hygrometer	Net radiation Windspeed Air pressure Air temperature Relative humidity	Calculation of FAO-56 potential ET for reference crop	Derivation of ET using crop coefficients (*need crop information) (Allen et al., 1998)

Evaporation pan	Class A pan	Depth of water	Calculation of evaporation of open water	N/A
Sap flow	Thermal dissipation probe	Movement of xylem sap	Calculation of plant transpiration (Lu et al., 2004)	N/A

Table S4: Metrics used for uncertainty assessment in the reviewed articles.

Name	Formula	Unit	Best value
Standard deviation (σ_y)	$$\sigma_y = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2}$$ Where y_i: estimate from remotely sensed data x_i: estimate of in situ data $\bar{y}$: average of y_i	Unit of x	0
Variance (σ_y^2)	$$\sigma_y^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2$$	Squared unit of x	0
Mean error (ME), Mean bias error (MBE), Bias	$$ME = \frac{1}{N}\sum_{i=1}^{N} y_i - x_i$$ Where x_i: estimate of in situ data	Unit of x	0
Relative error (RE) or Mean error percentage (MEP) or Percent Bias (PBIAS)	$$MEP = \frac{ME}{\bar{x}} \times 100$$	%	0
Normalized mean bias (NMB)	$$NMB = \frac{ME}{\sigma_x}$$	-	0
Mean absolute error (MAE) or Mean absolute difference (MAD)	$$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i - y_i\rvert$$	Unit of x	0
Mean absolute percentage error	$$MAPE = \frac{MAE}{\bar{x}} \times 100$$	%	0

(MAPE) or Mean absolute percentage difference (MAPD)	$MAPE = \frac{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i - y_i \rvert}{\bar{x}} \times 100$		
Pearson's coefficient of correlation (ρ)	$\rho = \frac{cov(x,y)}{\sigma_x \sigma_y} = \frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2 \sum_{i=1}^{N}(y_i-\bar{y})^2}}$	-	1
Regression coefficient: slope a	$a = \frac{N\sum_{i=1}^{N}(x_i y_i) \sum_{i=1}^{N}(x_i) \sum_{i=1}^{N}(y_i)}{N\sum_{i=1}^{N}(x_i)^2 \left(\sum_{i=1}^{N}(x_i)\right)^2}$	-	1
Regression coefficient: intercept b	$b = \frac{\sum_{i=1}^{N}(y_i)\sum_{i=1}^{N}(x_i)^2 - \sum_{i=1}^{N}(x_i)\sum_{i=1}^{N}(x_i y_i)}{N\sum_{i=1}^{N}(x_i)^2 \left(\sum_{i=1}^{N}(x_i)\right)^2}$	-	0
Coefficient of determination (R^2)	$R_1^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(x_i-\bar{x})^2}$	-	1
	$R_2^2 = \frac{\sum_{i=1}^{N}(y_i-\bar{x})^2}{\sum_{i=1}^{N}(x_i-\bar{x})^2}$	-	1
	$R_6^2 = \rho^2 = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^2(y_i-\bar{y})^2}{\sum_{i=1}^{N}(x_i-\bar{x})^2\sum_{i=1}^{N}(y_i-\bar{y})^2}$	-	1
	$R_7^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(x_i)^2}$	-	1
Mean squared error (MSE)	$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2$	Unit of x	0
Systematic MSE	$MSE_s = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - x_i)^2$ Where $\hat{y}_i$: estimate of y_i based on the ordinary least-squares regression $\hat{y}_i = a + bx_i$	Squared unit of x	0
Unsystematic MSE	$MSE_u = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$ Where $\hat{y}_i$: estimate of y_i based on the ordinary least-squares regression $\hat{y}_i = a + bx_i$	Squared unit of x	0

Root mean squared error (RMSE)	$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2}$$	Unit of x	0
Systematic RMSE	$$RMSE_s = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - x_i)^2}$$ Where $\hat{y}_i$: estimate of y_i based on the ordinary least-squares regression $\hat{y}_i = a + bx_i$	Unit of x	0
Unsystematic RMSE	$$RMSE_u = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$ Where $\hat{y}_i$: estimate of y_i based on the ordinary least-squares regression $\hat{y}_i = a + bx_i$	Unit of x	0
Normalized RMSE or fractional RMSE	$$RMSE_n = \frac{RMSE}{\sigma_x}$$	-	0
Relative RMSE	$$RMSE_r = \frac{RMSE}{\bar{x}} \times 100$$	%	0
Centered or Unbiased RMSE	$$RMSE_c = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(x_i - \bar{x}) - (y_i - \bar{y})]^2}$$	Unit of x	0
Coefficient of variation (CV)	$$CV_y = \frac{\sigma_y}{\bar{y}}$$	-	
Nash-Sutcliffe Efficiency (NSE)	$$NSE = 1 - \frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}(x_i - \bar{x})^2}$$	-	1
Index of agreement (d_2)	$$d_2 = 1 - \frac{\sum_{i=1}^{N}\omega_i(y_i - x_i)^2}{\sum_{i=1}^{N}\omega_i(\lvert y_i - \bar{y}\rvert + \lvert x_i - \bar{x}\rvert)^2}$$ ω_i: irregularly weight that represent relative size of the i^{th} interval or cell size.	-	1
Modified index of agreement (d_1)	$$d_1 = 1 - \frac{\sum_{i=1}^{N}\omega_i\lvert y_i - x_i\rvert}{\sum_{i=1}^{N}\omega_i(\lvert y_i - \bar{y}\rvert + \lvert x_i - \bar{x}\rvert)}$$ ω_i: irregularly weight that represent relative size of the i^{th} interval or cell size.	-	1
Taylor skill score (TSC)	$$TSC = \frac{4(1+\rho)}{\left(\hat{\sigma}_f + \frac{1}{\hat{\sigma}_f}\right)^2 (1+\rho_0)}$$ Where $$\hat{\sigma}_f = \frac{\sigma_y}{\sigma_x}$$ ρ_0: Maximum attainable correlation ($\hat{\sigma}_f \to 1,\ \rho \to \rho_0$)	-	4
Kling-Gupta Efficiency (KGE)	$$KGE = 1 - \sqrt{(\rho - 1)^2 + \left(\frac{\sigma_y}{\sigma_x} - 1\right)^2 + \left(\frac{\bar{y}}{\bar{x}} - 1\right)^2}$$	-	1

Standard error (SE)	$$SE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N-1}}$$	Unit of x and y	0
Similarity index (Ω)	$$\Omega = \frac{m\sigma_b^2 - \sigma^2}{(m-1)\sigma^2}$$ Where m: number of ensemble members σ^2: total variance of all members concatenated σ_b^2: variance of the time series that results from calculating the ensemble mean of each time step	-	1
Spatial Efficiency (SPAEF)	$$SPAEF = 1 - \sqrt{(\rho-1)^2 + \left(\frac{CV_y}{CV_x} - 1\right)^2 + (\gamma-1)^2}$$ $$\gamma = \frac{\sum_{i=1}^{N} min(K_i, L_i)}{\sum_{i=1}^{N} K_i}$$ Where γ: histogram matching term K: histogram of reference map L: histogram of simulated map	-	1
Median symmetric accuracy (MSA)	$$MSA = 100(e^{M(\lvert(Q)\rvert)} - 1)$$ Where M: median of the data $$Q = \frac{y}{x}$$	%	0
Degree correlation (r_l)	$$r_l = \frac{1}{\eta}\sum_{m=0}^{l}(C_{A_{lm}}C_{B_{lm}} + S_{A_{lm}}S_{B_{lm}})$$ $$\eta = \sqrt{\sum_{m=0}^{l}(C_{A_{lm}}^2 + S_{A_{lm}}^2)}\sqrt{\sum_{m=0}^{l}(C_{B_{lm}}^2 + S_{B_{lm}}^2)}$$ Where $C_{A_{lm}}$ and $S_{A_{lm}}$ are spherical harmonic coefficients of degree l and order m of dataset A $C_{B_{lm}}$ and $S_{B_{lm}}$ are spherical harmonic coefficients of degree l and order m of dataset B	-	1

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